FINAL REPORT

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Estimating Numbers of Wolves, Wolf Packs, and Breeding Pairs in Montana Using Hunter
Survey Data in a Patch Occupancy Model Framework

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EXECUTIVE SUMMARY

Reliable knowledge of the status and trend of carnivore populations is critical to their conservation. Direct and indirect methods of monitoring carnivores, however, are time consuming and expensive to conduct across large spatial scales. In the Northern Rocky Mountains, wildlife managers need a time- and cost-efficient method for monitoring the large, growing population of gray wolves (*Canis lupus*) at state-wide scales. Each year, Montana Fish, Wildlife and Parks (MFWP) conducts annual telephone surveys of >50,000 hunters providing a large number of potential observers of wolves in every part of Montana. We explored how survey data on hunter's sightings of wolves could be incorporated into multi-year patch occupancy models to estimate the abundance and distribution of wolf packs, wolves, and breeding pairs in Montana for 2007- 2009. We used hunter observations of wolves to estimate the probability that 600-km² patches within a uniform grid overlaid on Montana were occupied by a wolf pack. Our occupancy modeling framework also allowed us to examine how geographic and ecological factors influenced a wolf pack's probability of occupancy, colonization, extinction, and detection. To generate estimates of numbers of wolves, we used

occupancy model output in combination with the mean number of wolves seen by hunters. To generate estimates of numbers of breeding pairs, we used occupancy model output in combination with data on the distribution of pack sizes. We assessed model accuracy by comparing our estimates of numbers of wolf packs, wolves, and breeding pairs to MFWP minimum known number of wolf packs, wolves, and breeding pairs. In the top occupancy model, occupancy was positively related to forest cover, rural road density, and elevation, colonization was positively related to forest cover, bull elk harvest, and the mean number of wolves seen, extinction was negatively related to the mean number of wolves seen, and detection was positively related to hunter effort and forest cover. Our models provided estimates of number of wolf packs, wolves, and breeding pairs that were accurate, generally exceeding of MFWP minimum counts for 2007-2009 by \leq 20% (i.e., accounting for wolves undetected by current monitoring). Lastly, we developed a modeling framework that will enable MFWP to evaluate alternative harvest and management strategies. The patch occupancy model we developed for harvest modeling will allow MFWP to explore how harvest influences wolf population dynamics in the state. Patch occupancy models based on hunter surveys provide accurate estimates number of wolves and breeding pairs at state-wide scales in a time- and costefficient manner. For these models to remain accurate in the future, complementary field monitoring of pack sizes and distributions will be required to ensure hunter sightings remain calibrated to wolf population dynamics. The harvest models we present offer the opportunity to evaluate effects of alternative harvest scenarios when setting wolf quotas, and to evaluate actual effects of implemented quotas on the Montana wolf population through an adaptive management framework.

Attachments:

- Appendix A; R-code for calculating confidence intervals for numbers of wolf packs and numbers of wolves.
- Appendix B; The probability each 600 km² patch in Montana, USA was occupied by a wolf pack numbers of wolves in 2007, 2008, and 2009.
- Appendix C; Rich, L. N. 2010. An assessment of factors influencing territory size and the use of hunter surveys for monitoring wolves in Montana. MS Thesis, University of Montana, Missoula.

INTRODUCTION

Gray wolves (*Canis lupus*) were extirpated from the western United States in the early 1900s as a result of bounty-induced killing and habitat loss (Mech 1970). In 1973, wolves were listed as endangered in the lower 48 states (except Minnesota) by the United States Fish and Wildlife Service (USFWS). Wolves began naturally recolonizing northwestern Montana from Canada in the early-1980s, and 66 wolves were translocated from Canada into Yellowstone National Park and central Idaho in 1995 and 1996 to enhance recovery (Bangs et al. 1998). The recovery goal for wolves in the Northern Rocky Mountains (NRM) was ≥300 wolves and ≥30 breeding pairs (i.e., an adult male and female that have produced ≥2 pups which survive until December 31 of their birth year; USFWS 1994), evenly distributed among the recovery areas (Central Idaho [CID], Greater Yellowstone [GYA], and northwestern Montana [NWMT]) for 3 consecutive years (USFWS 1994). The wolf population in the NRM has exceeded this goal since 2002 (USFWS 2003). In 2009, the NRM wolf population was delisted (USFWS 2009) and a wolf hunting season was implemented in both Montana and Idaho. The decision to delist was revoked

in August 2010, and the species currently remains under protection of the Endangered Species Act (ESA).

To monitor wolves in the NRM during recovery, the USFWS and state agencies attempted to capture and radio-collar members of as many wolf packs as possible (USFWS et al. 2010). Radio collars were used to locate packs and document pack size, reproductive success, and territory size (USFWS et al. 2010). This monitoring technique was reliable when a small number of wolf packs inhabited the NRM; as of 2009, however, the NRM contained >1,700 wolves in >240 packs (USFWS et al. 2010). Radiotelemetry as a primary monitoring technique for this large, growing population is no longer feasible given the time and financial constraints of most management agencies. Nonetheless, state agencies in Montana, Idaho, and Wyoming will be legally required to monitor wolf populations and annually document \geq 100 wolves and \geq 10 breeding pairs within their respective states for 5 years following delisting (USFWS et al. 2010). To accomplish this, wildlife managers need a new, time- and cost-efficient method for accurately and precisely estimating numbers of wolf packs, total wolves, and breeding pairs at statewide scales.

Most carnivores, including gray wolves, are difficult to monitor on large spatial scales because they live at low densities, are often nocturnal, and are difficult to observe (Harrington and Mech 1982, Crete and Messier 1987, Schonewald-Cox et al. 1991, Ballard et al. 1992, Mills 1996). Monitoring wolves across the rugged and densely forested landscape of Montana has become prohibitively difficult as wolf numbers continue to increase. A variety of effective field survey methods (e.g., rendezvous site surveys, hair/scat genetic sampling, and howlboxes) have been developed for monitoring wolves (Harrington and Mech 1982, Crete and Messier 1987, Ballard et al. 1992, Becker et al. 1998, Gompper et al. 2006, Ausband et al. 2009), yet most of

these techniques are impractical to apply at a statewide level given constraints on personnel, time, accessibility, and budgets (Potvin et al. 2005).

In contrast, hunters are widespread and numerous during deer (*Odocoileus* spp.) and elk (*Cervus elaphus*) hunting seasons in Montana providing a large number of potential observers of wolves in every part of the state. Each year, Montana Fish, Wildlife and Parks (MFWP) conducts annual telephone surveys of >50,000 hunters to gather information about hunter success and other aspects of wildlife management. Preliminary work by Ausband et al. (2009) indicated that patch occupancy models (MacKenzie et al. 2006) developed using public sightings of wolves provided estimates of numbers of wolf packs that were consistent with known numbers of wolf packs in several study areas in Idaho. This suggests that in an appropriate modeling framework, these data may be reliable for use in population estimation. In anticipation of using similar survey data in future monitoring efforts, MFWP began asking questions pertaining to hunter's sightings of wolves as part of their telephone surveys beginning in 2007.

In recent years, patch occupancy models (MacKenzie et al. 2006) have become widely used for estimating the probability that landscape patches are occupied by a species of interest (i.e., occupancy) using detection/non-detection data. To estimate occupancy, investigators conduct repeated surveys of landscape patches during a relatively short time period (i.e., season) when occupancy is assumed to remain constant (MacKenzie et al. 2002). Patch occupancy modeling uses the patterns of detections and nondetections over multiple visits to each patch to estimate detection probabilities (i.e., probability species will be detected given that it is present) and occupancy. By including detection probabilities in estimates of occupancy, patch occupancy models account for imperfect detection of the species of interest (MacKenzie et al. 2006).

Patch occupancy models are based on a number of assumptions. First, detection probability is assumed to be independent at each patch. Second, occupancy is constant between repeated sampling occasions within a single season. Occupancy models can be developed for a single year or repeated sampling occasions from >1 year can be combined in a multi-year model. For multi-year models, occupancy of specific patches may change between years, but not within repeated sampling occasions in any given year. In the multi-year model, the probability that an unoccupied patch will become occupied (colonization) or the probability that an occupied patch will become unoccupied (extinction) can also be estimated (MacKenzie et al. 2006). The third assumption is that no heterogeneity in detection, occupancy, colonization, or extinction exists that cannot be explained by model covariates. Lastly, whereas patch occupancy models are specifically designed to account for imperfect detection, they assume that observations include no "false positive" detections (i.e., observers reporting a species when it is not present).

In territorial species, occupancy models can be used to estimate the abundance and distribution of territorial individuals or groups (MacKenzie et al. 2006). Territories are generally occupied exclusively by a single territorial individual or group (Powell 2000). When patch size is approximately equal to territory size, each occupied patch can, on average, be assumed to contain a single territorial individual or group (MacKenzie et al. 2006). The sum of occupancy estimates across all patches is thus an estimate of the total number of territorial individuals or groups (MacKenzie et al. 2006).

Our goal was to create a time- and cost-effective monitoring protocol for wolves in Montana that would provide estimates of numbers of wolves, wolf packs, and breeding pairs that are sufficiently accurate and precise to meet delisting criteria. Our first objective was to develop a multi-year patch occupancy model using hunter observations of wolves that accurately

estimated statewide and regional numbers of wolf packs for 2007-2009. Our models evaluated alternative hypotheses regarding ecological, geographic, and human-related factors that could influence wolf pack detection, occupancy, colonization, and extinction probabilities across the state. Our second objective was to estimate statewide and regional numbers of wolves for 2007-2009. We evaluated whether we could use patch-specific occupancy estimates of wolf pack presence and patch-specific observations of mean number of wolves seen by hunters to generate accurate estimates of the total number of wolves. Our third objective was to estimate numbers of breeding pairs based on our occupancy model estimates of number of wolf packs and existing data on the distribution of wolf pack sizes in Montana. To evaluate the accuracy of our models, we compared our estimates of numbers of wolf packs, wolves, and breeding pairs to MFWP's minimum known number of wolf packs, wolves, and breeding pairs.

Our final objective was to develop a modeling framework that will enable MFWP to evaluate alternative harvest and management strategies in an adaptive management framework. Adaptive management is a formal, systematic approach through which wildlife management efforts can be improved by learning from management outcomes. This process allows managers to forecast the effects of management plans under alternative models and then compare forecasted estimates to post-management population estimates to evaluate their effectiveness in meeting desired goals.

METHODS

Modeling Framework

Patch occupancy models provided the overall framework for all analyses conducted in this report. We used occupancy models to estimate the probability that landscape patches contained a wolf pack. While individual wolves may die, join, or leave a particular pack, we assumed the occupancy status (presence or absence) of an entire pack remained constant during our annual 5 week survey periods. We divided the survey period into 5, 1-week sampling occasions to obtain the repeated sampling required for occupancy modeling. Annual numbers of wolf packs estimated from our occupancy models provided the foundation for estimating numbers of wolves and numbers of breeding pairs.

To estimate numbers of wolf packs from 2007 to 2009, we used multi-year occupancy models developed in Program PRESENCE 3.0 (http://www.mbr-pwrc.usgs.gov.software.html; MacKenzie et al. 2006). In addition to estimating occupancy probabilities (ψ), multi-year models provided estimates of the probabilities of unoccupied patches becoming occupied in the subsequent year (local colonization [γ]) and occupied patches becoming unoccupied in the subsequent year (local extinction [ϵ]), thus enabling us to track dynamic population processes over time. The multi-year occupancy model uses encounter histories to estimate occupancy, local colonization, local extinction, and detection probabilities (p; MacKenzie et al. 2006). Encounter histories are records of whether or not wolves were sighted in individual patches by individual hunters during each sampling occasion. Detections and non-detections are recorded as a sequence of 1s and 0s indicating whether wolves(s) were observed (1) or not (0; Table 2).

We used covariates to account for hypothesized spatial variation in model parameters, and to evaluate a number of *a priori* hypotheses regarding factors that may influence occupancy, colonization, extinction, and detection probabilities (Table 1). Given that there were four model parameters to estimate, we used a multi-step process to identify our top model(s). We modeled detection probability first, followed by occupancy, colonization, and extinction. For each parameter, we identified the best model and then used that model structure when evaluating alternative model forms for each additional parameter. We first evaluated univariate models for

each parameter, where we had *a priori* hypotheses regarding how the covariates would affect the parameter of interest. After determining the best univariate model for a given parameter, we then considered combinations of covariates in the top univariate models that made biological sense and did not include covariates that were highly correlated (r < 0.70). In all cases, we used Akaike's Information Criterion (AIC) to rank models (Burnham and Anderson 2002). Our final top model was the model with the lowest AIC value that had parameter estimates (β) with 95% confidence intervals (CI) that did not overlap 0. We chose not to retain covariates with β estimates that overlapped zero because these parameters minimally improved model fit (Arnold 2010).

Hunter Surveys

We used hunter survey data to develop an encounter history database to estimate numbers of wolf packs. In Montana, MFWP has historically conducted annual phone surveys of a random sample of resident deer and elk license holders. Approximately 50-80,000 hunters are surveyed annually. Beginning with the 2007 hunting season, the following questions were added to the survey: 1) "Did you see ≥1 live wolf or wolves while hunting between September 1 and January 15?", and 2) "If yes, provide the hunting district where you saw wolves, the number of wolves you saw, a landmark close to where wolves were seen, and the date when you saw wolves?" We obtained 2007-2009 hunter survey data from MFWP.

We used the 5-week deer and elk rifle season as our survey period. Each week represented a sampling occasion (i.e., 5, 1-week sampling occasions) and we assumed occupancy of patches by wolf packs remained constant during the 5 week survey period. In 2007, the survey period was from 21 October to 25 November. In 2008 and 2009, the survey period was from 26 October to 30 November. Because we were interested in estimating occupancy for

established wolf packs (i.e., a group of ≥ 2 wolves traveling together in a defined territory; Fuller et al. 2003), we only included visual observations by individual hunters of 2-25 wolves in our dataset. We dropped observations of single wolves because they did not meet the definition of an established wolf pack and were more likely misidentifications (i.e., species seen was a coyote [C. latrans]). We dropped observations of >25 wolves because they were likely exaggerations or people reporting wolves from multiple sighting occasions. We created point locations for individual hunter observations based on the provided landmarks (e.g., creeks, mountains, and towns) using National Geographic TOPO! software (NGHT, Inc., Evergreen, CO). We were able to locate correct landmarks on the map relatively quickly by refining our search to the hunting district where the wolves were seen. When the name of a creek or minor river was provided as a landmark, we plotted point locations at the creek or river's confluence. When we could not clearly find the referenced locations (poor description, site that did not appear to exist), we dropped that observation from the wolf locations database (<5% of locations). We imported point locations into ArcGIS 9.3.1 (E.S.R.I., Redlands, CA) for analyses.

After developing point files of hunter observations, we overlaid these points on a 600 km² grid spanning the state of Montana and assigned locations to individual grid cells. We used a 600 km² grid cell size because it was equal in area to mean wolf pack territory size in Montana (Rich 2010; Figure 1, Appendix C). For each patch, we recorded a "1" for each sampling period where at least 3 hunters saw a minimum of 2 wolves each and a "0" for sampling occasions where detection criteria were not met (Table 2). Encounter histories were copied and pasted directly into Program PRESENCE 3.0 for analyses.

Assessing false positives in hunter survey data

We were aware that data on sightings of wolves by surveyed hunters were likely to contain observations that were 1) not wolves, but coyotes; 2) overestimates or exaggerations of numbers of wolves seen; and 3) observations reported for areas where wolves were not actually present. Occupancy models assume that detections of a species indicate "presence" (MacKenzie et al. 2002). Consequently, we investigated several approaches for reducing the number of false positive observations in our dataset. Rich (2010) evaluated how classifying a patch as occupied based on different minimum numbers of hunters observing ≥2 wolves in that patch affected occupancy estimates (Figure 2). She compared estimates of wolf packs using these different encounter histories with MFWP minimum known number of wolf packs to determine which datasets provided estimates comparable to MFWP data. Based on results from Rich (2010), this report focuses on multi-year models that only classified a patch as occupied if ≥3 hunters reported seeing ≥2 wolves in a sampling occasion.

To further evaluate the effectiveness of this approach, we estimated the rates of false positive observations in three datasets (all observations, observations where ≥ 2 hunters saw ≥ 2 wolves in a given sampling occasion, and observations where a ≥ 3 hunters saw ≥ 2 wolves in a given sampling occasion) using software developed by David Miller (Patuxent Wildlife Research Center, USGS, Laurel, MD; Miller et al. *in review*). The program estimates false positive rates using both the Royle and Link (2006) approach and the technique developed by Miller et al. *(in review)*.

Model Covariates

Multi-year occupancy models can contain both site-specific and survey-specific covariates for occupancy, local colonization, local extinction, and detection probabilities. Site-specific covariates are factors (e.g., percent forest cover) that vary across patches, but do not

change from year to year (i.e., survey periods) or week to week (i.e., sampling occasions).

Survey-specific covariates (e.g., hunter effort) can vary across patches and between years, but do not change between weekly sampling occasions. Occupancy models can also contain covariates that vary among weekly sampling occasions. We did not consider any week-specific covariates with the exception of examining differences in detection among weeks because weather conditions and vegetation cover, which may influence a hunter's ability to detect wolves, often change over the 5 week rifle season.

We assessed 5 site-specific covariates and 7 survey-specific covariates in our models (Table 1). We hypothesized that environmental features such as forest cover, elevation, and slope could influence occupancy, colonization, and local extinction rates of wolf packs because wolves select for forested areas (Mladenoff et al. 1995, Mladenoff and Sickley 1998, Oakleaf et al. 2006, Jedrzejewski et al. 2008) with low elevations and slopes (i.e., low levels of ruggedness; Paquet et al. 1996, Oakleaf et al. 2006, Whittington et al. 2008) where ungulates are more accessible and abundant (Table 1). Forest cover could also influence detection probability; either positively because hunters are more abundant in forests or negatively because wolves are harder to see in forests (Table 1). We estimated percent forest cover in each patch by reclassifying 90m² land cover pixels (Gap Analysis Project, Wildlife Spatial Analysis Lab, University of Montana) into forest and non-forest. We derived slope and elevation data from 200m² resolution digital elevation models (DEM; USGS National Elevation Dataset). We used the vector ruggedness measure developed by Sappington et al. (2007) to assess terrain ruggedness (TRI). We chose this measure of ruggedness because it was less correlated with slope than other methods. We used Terrain Tools in ArcToolbox to calculate this metric using the 200m² DEM. We used a 3x3

neighborhood to calculate TRIs and for each 600 km² grid cell, we computed mean TRI*100 as unscaled TRI values were quite small.

We hypothesized that occupancy, colonization, and local extinction rates of wolf packs could also vary with road densities because wolves are often less abundant in areas with high road densities (Mech et al. 1988, Ballard et al. 1998, Mladenoff and Sickley 1998, Jedrzejewski et al. 2008; Table 1). Roads can fragment wolf habitat and provide access to humans who legally, illegally, or accidentally kill wolves (Mech et al. 1988, Fuller 1989, Mladenoff et al. 1995, Carroll et al. 2001, Fuller et al. 2003). Selection or avoidance of roads by wolves, however, depends on whether roads have high or low human activity (Whittington et al. 2008). Wolves often use low-use roads as travel corridors (Thurber et al. 1994, Paquet et al. 1996, Whittington et al. 2008; Table 1). Road densities could also influence p because roads likely increase hunter access (Table 1). We classified roads (U.S. Census Bureau Geography Division 2003 and USDA Forest Service 2007) as four-wheel drive (4WD; i.e., roads for vehicles with high ground clearance) or two-wheel drive (2WD; i.e., roads suitable for passenger cars) and eliminated all roads in areas with human population densities >25 people/km² based on the assumption that these roads represented high-use roads. We then calculated low-use 4WD road densities and low-use 2WD road densities (km of roads/km²) using Spatial analyst in ArcGIS 9.3.1.

Survey-specific covariates included buck deer harvest, bull elk harvest, hunter effort for elk, hunter effort for deer, sheep density, cattle density, and average number of wolves observed per grid cell (Table 1). All of these factors varied across but not within years. We hypothesized that occupancy, colonization, and local extinction rates would vary with prey density because wolf densities are positively correlated with ungulate densities (Messier 1985, Fuller and Murray)

1998, Fuller et al. 2003; Table 1). We used buck deer and bull elk harvest per km² as indices of deer and elk density because estimates of deer and elk abundance were not uniformly available across Montana. Harvest of antlered deer and elk are often positively correlated with deer and elk abundance and may be an indirect, general indicator of population level when no direct estimates are available (Wood et al. 1989, Hamlin and Ross 2002, Dusek et al. 2006). We calculated annual buck deer and bull elk harvest density for each hunting district using ungulate harvest statistics from MFWP (MFWP 2010). In reservations and national parks, where hunting was not permitted or MFWP did not have harvest information (i.e., national parks and reservations), we estimated indices of deer and elk density by averaging buck deer and bull elk harvest densities in hunting districts along their respective borders. We also used ungulate harvest statistics from MFWP to calculate annual hunter effort for elk (hunter days for elk/ km²) and hunter effort for deer (hunter days for deer/km²) in each hunting district. We hypothesized that detection of wolves by hunters would increase with hunter effort (Table 1).

Wolves generally select for areas with low livestock densities at the home range scale (Oakleaf et al. 2006; Table 1) possibly because management selects against wolf packs that prey on livestock through lethal control (Sime et al. 2010). We therefore hypothesized that occupancy and colonization would be negatively associated with livestock density, while local extinction would increase with higher livestock densities (Table 1). We used U.S. Department of Agriculture livestock statistics to estimate annual cattle and sheep densities by county (U.S.D.A. National Agricultural Statistics Service 2010). We excluded wilderness areas and national parks from counties to ensure livestock density estimates only encompassed areas where grazing was permitted.

Lastly, we hypothesized colonization and local extinction rates would vary with the mean number of wolves seen by hunters (\overline{x}_{wolf}) because as the number of wolves traveling in a patch increase, the likelihood the patch will be colonized by a wolf pack should also increase (Table 1). MFWP hunter surveys recorded numbers of wolves observed by individual hunters. We summarized these data by grid cell concurrent with building encounter history files. We calculated mean, median, mode, and maximum values for wolves in each grid cell using the Data \rightarrow Subtotal function in Excel (Table 2). Because we only classified a patch as occupied if \geq 3 hunters saw \geq 2 wolves in a given week, patches that were not occupied by a wolf pack during a year often had a value for mean number of wolves that was greater than zero.

Estimating wolf packs

We evaluated multi-year occupancy models using Program PRESENCE 3.0 (http://www.mbr-pwrc.usgs.gov.software.html; MacKenzie et al. 2006). We used the initial occupancy (2007), local colonization, local extinction, and detection model parameterization which provided occupancy estimates for 2008 and 2009 as derived parameters. PRESENCE provided patch-specific estimates, standard errors, and upper and lower 95% confidence limits of initial ψ (2007), derived ψ (2008, 2009), γ (2007-2008, 2008- 2009), ε (2007-2008, 2008- 2009), and ρ (2007, 2008, 2009).

Once models were run in PRESENCE, we exported the individual model output file from the top model to Excel. We used the sum of occupancy values across all patches (statewide and by wolf management unit [WMU]) as our estimate of total number of wolf packs. Our final estimates of total number of wolf packs were adjusted for both partial cells on the border and included estimates for reservations and national parks. For patches along the state border, not wholly contained within the state, we scaled the occupancy value by the proportion of the patch

contained within the state. A small number of patches (i.e., national parks and reservations) had covariate data, but no hunter survey data as they were not under MFWP jurisdiction for deer and elk harvest. In these cases, we used the recursive conditional occupancy equation (MacKenzie et al. 2006, Equation 7.4) and covariate values for these cells to estimate occupancy.

Estimating total number of wolves

To estimate total numbers of wolves (statewide, WMU), we multiplied the patch-specific occupancy probabilities by \bar{x}_{wolf} per grid cell and summed these values across the area of interest.

Confidence intervals for wolf packs and total wolves

We used a Monte Carlo bootstrap approach to estimate 95% confidence limits for our estimates of numbers of wolf packs and total numbers of wolves using the UNMARKED package in Program R. Using this approach, we resampled the encounter histories and associated covariates 10,000 times, ran the top model structure to obtain estimates of numbers of packs (or numbers of wolves), and calculated the upper and lower bounds (Appendix A: R code for calculating confidence intervals for numbers of packs, numbers of wolves).

Estimating numbers of breeding pairs

In order to estimate numbers of breeding pairs, we first needed to estimate the distribution of pack sizes. While our occupancy model approach for estimating numbers of wolf packs and numbers of wolves is valid on a statewide and regional level, these models are not designed to estimate sizes of individual wolf packs. Because our method for estimating the probability of a wolf pack containing a breeding pair is dependent on individual pack size (Mitchell et al. 2008), we used data on the distribution of pack sizes from known packs to estimate the distribution of wolf packs sizes for our modeled estimates of numbers of packs. We

used data on pack size distributions from known wolf packs for 2005-2009 for the 3 recovery areas in Montana. We determined the proportion of packs in 15 size classes ranging from <2 wolves to >15 wolves. We then estimated the number packs in each size class by applying the region-specific proportions (and associated variances) to the numbers of wolf packs obtained from our occupancy models.

Mitchell et al. (2008) used logistic regression generated models to relate the probability of a wolf pack containing a breeding pair to pack size for the 6 recovery regions (3 regions in Montana) for the Northern Rocky Mountains. We used the region-specific probability curves for the Southwest Montana - Greater Yellowstone Experimental Population Area (GYA), Southwest Montana - Central Idaho Experimental Population Area (CID), and Northwest Montana Recovery Areas (NWMT) (Mitchell et al. 2008), and our estimated pack size distributions to obtain estimates of the numbers of breeding pairs in Montana for 2007-2009.

Model Evaluation

We compared our estimates of numbers of wolf packs, wolves, and breeding pairs to MFWP's minimum known number of wolf packs, wolves, and breeding pairs for model validation. In the early years of recovery and reintroduction, when the number of packs, wolves, and breeding pairs in Montana were small, minimum counts approximated a census. As the wolf population has grown, monitoring capacities have likely been exceeded, such that in recent years minimum counts have increasingly under-represented population size to an unknown extent. Nonetheless, we did not expect the difference between minimum counts and the true number of wolf packs, wolves, and breeding pairs to be substantial. We expected estimates would be greater than but close to minimum counts. Although an under-representation of population size, minimum counts represented the best available information, which was at a level of detail

unavailable for nearly any other carnivore population at a statewide scale, and thus a reasonable standard for evaluating estimates.

RESULTS

Hunter Surveys

In 2007, 50,370 deer and elk hunters were surveyed by MFWP; 2.4% (1,207) saw \geq 2 wolves during the 5-week survey period. In 2008, 82,411 hunters were surveyed; 3.48% (2,870) saw \geq 2 wolves during the 5-week survey period. In 2009, 81,117 hunters were surveyed; 3.07% (2,486) saw \geq 2 wolves during the 5-week survey period. Mean numbers of wolves seen by hunters increased over time, with hunters seeing an average of 1.05 wolves (SD 1.48) across all grid cells in 2007, 1.72 wolves (SD 2.73) in 2008, and 1.89 wolves (SD 2.89) in 2009.

False positives

We found 6.33-8.73% of all hunter sightings of wolves (i.e., using the complete data set) were likely false positives. When we classified patches as occupied if ≥ 2 wolves were seen by ≥ 2 hunters in a week, the false positive rate decreased to 0.35-0.48%. By classifying patches as occupied if ≥ 2 wolves were seen by ≥ 3 hunters in a week, the false positive rate dropped below 0.0005% for all years. By classifying patches as occupied if ≥ 2 wolves were seen by ≥ 3 hunters in a week we minimized false positives. We did not rarify the data further because doing so would not reduce false positives substantially and would likely increase false negatives.

Estimating wolf packs

Detection probability was high ($\bar{p} = 0.23$, $x_{min} = 0.06$, $x_{max} = 0.92$, SE = 0.024) across Montana from 2007-2009. The top model showed a positive relationship between the probability that a wolf pack occupied a patch and forest cover, elevation, and low-use 2WD roads (Table 4). One model was within 4 Δ AIC of the top model (Table 3); however, only the top model had

parameter estimates with 95% CIs that did not overlap 0. We therefore used our top model for estimating numbers of wolf packs. The probability that an unoccupied patch would become occupied by a wolf pack in the following year was positively related to forest cover, bull elk harvest, and \bar{x}_{wolf} (Table 4). The probability that an occupied patch would become unoccupied in the following year was negatively related to \bar{x}_{wolf} (Table 4). Lastly, the probability that a wolf pack would be seen by a hunter was positively related to hunter effort for elk and forest cover, and this probability changed between sampling occasions (Table 4).

Our top occupancy model estimated there were 82 (SE = 31), 124 (SE = 28), and 145 (SE = 28) wolf packs compared to MFWP minimum counts of 82, 102, and 118 wolf packs in Montana in 2007, 2008, and 2009, respectively. The minimum number of wolf packs known to be in Montana was equal to the occupancy estimate in 2007 and fell within the lower half of the 95% CIs for occupancy estimates in 2008 and 2009 (Figure 2). Maps showing distribution of estimated wolf packs are located in Appendix B. In addition to statewide estimates, we also estimated numbers of wolf packs by WMU (Figure 4A).

Estimating total number of wolves

Our top model underestimated numbers of wolves for 2007 (\bar{x} = 170, 95% CI: 118-232, FWP min = 422) but provided estimates for 2008 (\bar{x} =470, 95% CI: 370-586) and 2009 (\bar{x} =590, 95% CI: 450-812) that were comparable to FWP minimums (497, 525 respectively). Because the model underestimated the number of wolves for 2007, we also examined estimates from the 2 hunter dataset for comparison (Figure 3). Total number of wolves for 2007 was still underestimated \bar{x} =233, 95% CI: 219-337), whereas the model for 2008 (\bar{x} = 708, 95% CI: 626-791) and 2009 (\bar{x} =779, 95% CI: 705-853) appeared to overestimate total numbers of wolves (Figure 3). Maps showing distribution of estimated numbers of wolves are located in Appendix

B. In addition to statewide estimates, we also estimated numbers of wolves by WMU (Figure 4B).

Estimating breeding pairs

Distribution of pack sizes for packs of known size in Montana for 2005-2009 (Figure 5A) indicated that the highest proportion of packs had ca. 4-6 wolves with considerably fewer packs containing >10 wolves. The distribution of pack sizes also varied by recovery region (NWMT, CID, GYA) (Figure 6). As expected, hunters generally observed fewer wolves than the known pack sizes for given areas (Figure 5B).

Our estimate for numbers of breeding pairs for 2007 (40 breeding pairs, 95% CI: 22-56) was close to the FWP minimum count of breeding pairs (29), whereas our estimates for 2008 (61, 95% CI: 36-88) and 2009 (70, 95% CI: 42-101) were somewhat higher (Figure 7).

Modeling Alternative Harvest Strategies

Whereas we were not able to evaluate harvest for 2007-2009, one of the objectives of our patch occupancy modeling approach was to develop a framework where alternative harvest/management strategies can be evaluated. Here we provide an example of how the 2007-2009 patch occupancy models and associated data can be used to project wolf population numbers for 2010 and provide a framework that can be used to evaluate alternative management/harvest options in the future.

The modeling procedure we have presented focuses on estimating current (or past) wolf numbers; however, this approach can also be used (with minor modifications) to evaluate potential effects of different management/harvest scenarios on future populations. Whereas we do not advocate trying to predict populations many years into the future, we believe that using

the current multi-year estimation framework (e.g. 2007-2009) is reasonable for evaluating effects of different scenarios on the subsequent (e.g. 2010) year's wolf population.

The basic procedure we have developed for estimating numbers of packs and numbers of wolves covered in this report has 2 main components: 1) use of patch occupancy models and encounter histories to estimate number of packs, and 2) combining cell specific occupancy estimates with data on numbers of wolves observed to estimate total wolf populations. The occupancy model predicts occupancy for individual grid cells based on the covariates included in the model. For example, the top model for 2007-2009 included effects of forest cover, elevation and low-use 2WD roads. Using the β estimates from the top model, we can derive 2007 occupancy values (initial occupancy) for any cell if we know the covariate values are using the following equation:

1. Logit (cell occupancy) = β (intercept) + β (forest) + β (low-use 2WD roads) + β (elevation)

We can also include effects of harvest/depredation removal on occupancy (and/or colonization/extinction) to evaluate alternative management strategies:

- 2. Logit(cell occupancy) = β (intercept) + β (forest) + β (low-use 2WD roads) + β (elevation) + β (harvest)
- 3. Logit(cell occupancy) = β (intercept) + β (forest) + β (low-use 2WD roads) + β (elevation) + β (removal)
- 4. Logit(cell occupancy) = β (intercept) + β (forest) + β (low-use 2WD roads) + β (elevation) + β (harvest) + β (removal)

Because we are using a multiyear model that incorporates dynamics processes, occupancy in subsequent years (e.g. 2010) can be projected using the recursive conditional occupancy equation (MacKenzie et al. 2006, Equation 7.4) where cell-specific occupancy is calculated as follows:

5. Logit(Occ (t+1)) = (occ(t) * (1-extinction(t))) + ((1-occ(t)) * colonization(t)))

The equation defining occupancy for the top model for 2007-2009 is shown above (Equation 2). For local colonization and extinction for our 2007-2009 model, the following equations apply:

- 6. Logit (Colonization) = β (intercept) + β (\overline{x}_{wolf}) + β (forest) + β (bull elk harvest)
- 7. Logit (Extinction) = β (intercept) + β (\overline{x}_{wolf})

If (t+1) = 2010, (t) = 2009 values for occupancy, colonization, and extinction. Program PRESENCE provides cell-specific estimates for all parameters listed above, so calculating projected values for 2010 is not difficult once Presence output is exported to a spreadsheet.

Factors such as forest cover, elevation, low-use 2WD road density are static covariates and do not change over time. For \bar{x}_{wolf} and bull elk harvest, however, we need to have reasonable projections for what these values will be in 2010. In addition to functioning as a covariate in the occupancy model, \bar{x}_{wolf} is also an important component of our model for estimating total numbers of wolves. For this exercise, we used average bull elk harvest values for 2007-2009 for use in the 2010 projection. As bull elk harvest numbers for individual hunter districts was relatively consistent across years for 2007-2009, we believed that the 2007-2009 average bull elk harvest was a reasonable estimate of bull elk harvest for 2010. For \bar{x}_{wolf} , on the other hand, we expect that this value is very likely to change over time. For \bar{x}_{wolf} , we developed

a regression equation to predict \bar{x}_{wolf} values across a range of vegetative, geographic, and management (removal) conditions that also includes a growth factor (year) reflecting the increased number of wolves reported by hunters from 2007-2009. The dependent variable in this model was grid cell specific \bar{x}_{wolf} values and the independent variables were the grid cell specific covariate values. The equation we used in this example is as follows:

8. \overline{x}_{wolf} (grid cell) = β (intercept) + β (forest) + β (elevation) + β (low-use 2WD roads) + β (year) + β (bull elk harvest) + β (depredation removal)

Regression model output from this equation is found in Table 5.

As with the occupancy equation, forest cover, elevation, and low-use 2WD road density did not vary by year. To project \bar{x}_{wolf} values for 2010, we used 2007-2009 mean values for bull elk harvest and depredation removals and year was stepped forward (4) to reflect the increasing time trend. Using grid-cell specific covariate values, we used the regression equation to project \bar{x}_{wolf} values for individual grid cells for 2010. It would also be possible to aggregate grid cells into similar areas (e.g. areas of similar forest cover and elevation) and use the regression equation to estimate \bar{x}_{wolf} values on a broader spatial scale.

Once we had projected 2010 values for cell-specific occupancy and \bar{x}_{wolf} , we were able to calculate the projected number of packs and projected numbers of wolves for 2010 (Figure 8). As with the basic occupancy modeling approach, we sum the projected occupancy values across the state to get an estimate of number of packs for 2010 and sum (occupancy* \bar{x}_{wolf}) values to get an estimate of number of wolves for 2010. If harvest or removal effects were components of the

model, we could compare alternative harvest strategies by comparing how total wolf packs and total numbers of wolves vary under alternative models.

DISCUSSION

The USFWS will require that state agencies within the NRM annually estimate wolf population size and distribution within their state for 5 years following removal of NRM wolves from the Endangered Species List (USFWS 2006). With delisting, however, federal funding previously available for intensive monitoring may decline, whereas logistical challenges may increase as the wolf population grows. At the same time, public expectations for wolf management after delisting will likely mean that MFWP and other state agencies will need to produce robust estimates of population size far into the future. Methods for directly or indirectly monitoring population abundance are costly and time-intensive, especially at state-wide scales (Crete and Messier 1987, Gros et al. 1996, Potvin et al. 2005, Gompper et al. 2006).

To provide a time- and cost-effective alternative to historical monitoring and estimation of NRM wolves, we developed a multi-season occupancy model using hunter surveys as the sampling method, that accurately estimated the abundance and distribution of wolf packs and wolves in Montana from 2007 to 2009 as well as a model that accurately estimated the abundance and distribution of breeding pairs. The multi-season occupancy model allowed us to estimate the probability each patch contained a wolf pack under the variety of ecological conditions found in Montana and to develop an understanding of the underlying population dynamics that may cause an unoccupied patch to become occupied or an occupied patch to become unoccupied (i.e., γ and ε rates; MacKenzie et al. 2006).

To generate accurate estimates of model parameters, we had to address the problem of false positives within the hunter survey data set. As we hypothesized, false positives decreased

as the number of hunters who saw ≥ 2 wolves in a patch increased. By only classifying a patch as occupied if ≥ 3 hunters saw ≥ 2 wolves, we were able to meet the occupancy modeling assumption that wolf packs were not falsely detected when absent and strike a balance between minimizing both false positives and false negatives.

To test model estimates, we compared them to MFWP's annual minimum known number of wolf packs, wolves, and breeding pairs. Although minimum counts did not estimate true population size, monitoring effort in the NRM had been sufficiently intensive (i.e., a large portion of the population was counted in any given year) that minimum counts were likely a reliable index of population size for wolves. Because a large proportion of the population was counted each year, we assumed minimum counts were not large underestimates of truth. This assumption was supported when we used a detection criterion that minimized both false positives and false negatives (i.e. classifying a patch as occupied if ≥ 3 hunters saw ≥ 2 wolves; Figure 2). The one exception was our estimate for total numbers of wolves in 2007. We estimated there were 170 wolves which was well below the minimum of 422. This underestimate may have occurred because there were ~30,000 fewer hunters surveyed in 2007 than in 2008 and 2009. It may also have occurred because there were more observations of single wolves, which were dropped from the occupancy analyses, in 2007 than in 2008 or 2009. Additionally, 2007 was the first year that hunters were asked about wolves on the telephone survey and were not yet accustomed to reporting wolf observations in this manner. The intensity of monitoring in Montana, which resulted in a detailed understanding of population size that is unprecedented for a large, wide-spread population of wolves (USFWS et al. 2010), made the likelihood that minimum counts were a misleading index or a strong under-representation of true population size relatively small.

Detection probability for a population of animals may be influenced by their local density, behavioral factors, seasonality, environmental factors, weather, or sampling effort (Royle and Nichols 2003, Bailey et al. 2004). Overall, our detection probabilities were high (\bar{p} = 0.23, SE = 0.024), indicating that hunter survey data can be used to provide reasonably precise estimates of occupancy and related parameters. Our results showed wolf packs were more likely to be seen by hunters in forested areas where hunter effort was high. The greater the hunter effort and forest cover in a patch, the greater the density of hunters and thus the relatively high probability that wolves were seen. The positive effects of low-use road densities on the ability of hunters to detect wolves was consistent with our hypothesis but support for it was relatively weak and uncertain (95% CI for coefficient included 0). We did not detect any year-to-year differences or time trends in detection rates for 2007-2009. To ensure their continued reliability, information from hunters needs to be periodically validated with field data.

The probability that an animal will occupy, colonize, or become locally extinct from an area is not constant across time or space and may vary predictably with local ecological factors. Previous studies have found wolves select forested areas (Mladenoff et al. 1995, Mladenoff and Sickley 1998, Oakleaf et al. 2006, Jedrzejewski et al. 2008) and use low-use roads as travel routes (Paquet et al. 1996, Whittington et al. 2008). We hypothesized wolf packs would be more likely to have established territories in areas with these features. As we hypothesized, the probability a site was occupied by a wolf pack increased with forest cover and low-use 2-wheel drive road density. These results suggest wolves prefer to establish territories where there is cover and a high density of accessible prey. Forests provide cover and tend to have more abundant prey and low-use roads could serve as travel corridors making the prey more accessible. Our finding that occupancy and elevation were positively correlated is likely

because the majority of wolves were found in western Montana where elevations were relatively high and generally absent from eastern Montana were elevations are relatively low.

We did not find occupancy to be influenced by bull elk and buck deer harvest densities. We assumed bull elk and buck deer harvest density were indices of deer and elk density, which may not have been valid if harvest density was more indicative of human access than ungulate densities. This violation would cause the effects of harvest density on occupancy to be negatively biased if pack occupancy decreased with increasing human access. Additionally, harvest of male ungulates may only be useful as a long-term indicator because weather conditions and harvest regulations can override population levels in influencing annual harvest (Hamlin and Ross 2002). It is possible that ungulate densities did not influence wolf pack occupancy if ungulate densities were high across western Montana. In the future, however, if ungulate densities decline with the increasing densities of wolves, they may become a more important determinant of site occupancy by wolf packs.

As we hypothesized, the probability an unoccupied patch was colonized by a wolf pack in the following year increased with percent forest cover, bull elk harvest density, and mean number of wolves seen by hunters. Assuming bull elk harvest density was a reliable index of elk density, these results show wolf packs were more likely to colonize forested areas with high densities of elk, the primary prey for wolves in the NRM (Bangs et al. 1998). Areas with high food accessibility likely result in increased nutritional levels of wolves which could increase their reproduction and survival (Fuller et al. 2003). Colonization likely increased with the mean number of wolves seen because the number of wolves in a patch should be positively related to the probability there was ≥ 1 male and ≥ 1 female that could pair up, reproduce, and establish a pack.

Overall, occupancy estimates of the abundance and distribution of wolf packs and wolves were consistent with the known abundance and distribution of wolf packs and wolves in Montana (Sime et al. 2010). There were several areas, however, where the occupancy model we developed estimated presence of wolf packs where none were known to be. For example, the model estimated wolf packs inhabited the Little Belt and Big Belt Mountains northwest and west of Helena, in the Helena National Forest between Helena and Butte, and the Beaverhead and Tendoy Mountains in southwest Montana (Appendix B). If accurate, this suggests continued spread of the wolf population in Montana into areas where wolves have yet to be documented or monitored.

Our estimates of breeding pairs were developed using pack size distributions for 2005-2009 for the 3 recovery regions in Montana. Variation in pack size distributions among years contributed to the fairly large confidence intervals for our breeding pairs estimates. Whereas we believed our estimates of breeding pairs for 2007-2009 were reasonable, accuracy of future estimates using this approach will be dependent on true pack size distributions remaining within this historic range. It is possible that the distribution of pack sizes may change as a region becomes saturated with wolves. Because we can calculate distributions for all 6 recovery regions across the NRM Region, we may be able to gain a better understanding of how pack size distributions change by comparing distributions in areas with established wolf populations to areas that have been recently colonized.

Harvest Modeling in Patch Occupancy Framework

Given the limited harvest data available for 2007-2009, we were limited in our ability to fully explore the potential of modeling harvest in a patch occupancy framework. The ability to detect an effect if it actually exists (power of a test), is a function of both sample size and the size

of effect we are hoping to detect. Given that harvest occurred only in 2009, and we anticipated the 2009 harvest effect to be evident on the 2010 wolf population, we cannot yet model harvest effects in an occupancy modeling framework. As additional years of data where wolf harvest occurs become available, we will be better able to explore how harvest influences wolf population dynamics in the state and address questions such as 1) Is harvest additive or compensatory? 2) Do depredation removals drive population dynamics? 3) Does prey availability determine wolf population levels? or 4) Are wolf population levels determined by a combination of these factors?

MANAGEMENT IMPLICATIONS

Patch occupancy models based on hunter observations of wolves can provide wildlife managers with the ability to estimate the number and distribution of wolf packs, wolves, and breeding pairs at a statewide and WMU level. These models can help state agencies achieve the USFWS recovery requirement of annually documenting the numbers of wolves and breeding pairs (i.e., packs that contain ≥ 2 adults and \geq pups on 31 December; USFWS 1994) within their respective states. A multi-season occupancy model can be used to ensure recovery objectives for the NRM wolf population continue to be met prior to delisting and to provide a reliable tool for documenting recovery criteria following delisting.

In addition to documenting recovery criteria, multi-season occupancy models can be used to monitor population trends and document new packs. Annual estimates of the number of packs, wolves, and breeding pairs can be compared to determine if the population is increasing, decreasing, or remaining the same. To the same effect, annual estimates of the proportion of area occupied by wolves (i.e., number of occupied patches / total number of patches) can be compared to evaluate changes in the spatial distribution of wolves. Because hunter survey data

is collected annually and the model's covariates are not temporally static, the occupancy model should detect if wolves appear in eastern Montana. To document new packs, state agencies can focus field efforts on patches where no known wolf packs existed but were identified as occupied by the occupancy model or had a high probability of colonization. Likewise, local extinction probabilities can be used to predict where wolf packs will have high turn-over rates.

Our occupancy model, similar to other models, should not be considered a temporally static model that can be used perpetually with confidence. The model requires periodic groundtruthing to ensure its continued reliability. Monitoring is needed to verify hunters' sightings continue to be dependable indicators of the presence of wolves. In the future, information provided by hunters may become less reliable because of waning interest or because of attempts to influence estimates by mischaracterizing their sightings. Territory sizes also need to be monitored because the accuracy of an occupancy model used to estimate the number of territorial animals or groups is dependent on the assumption that patch size is equal in area to mean territory size (MacKenzie et al. 2006). If territory sizes change as the density of wolves continues to increase and wolf management becomes more intensive following desliting occupancy estimates based on territory sizes we observed could become biased. Lastly, the distribution of pack sizes needs to be monitored to ensure continued reliability of breeding pair estimates; the distribution of pack sizes may change as a recovery region becomes saturated with wolves. Development of an occupancy model based on multiple survey methods (e.g., hunter surveys, scat, track, and howl surveys; Nichols et al. 2008) is needed. Fine-scale survey methods (Ausband et al. 2009; Stenglein et al. 2010) could be used in conjunction with hunter surveys to ensure future occupancy estimates are robust to weaknesses or changes in any one methodology.

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Table 1. Mean values of covariates included in multi-year occupancy models for gray wolf packs in Montana, 2007-2009 and hypothesized relationships between covariates and a wolf pack's probability of occupancy (ψ), local colonization (γ), local

extinction (ε), and detection (p) by a hunter.

	All :	All years		2007		2008		2009		Hypothesized			
Model Covariate ^a								1	elatio	nship ^b	ı		
	$\overline{\overline{x}}$	SE	\overline{x}	SE	\overline{x}	SE	\overline{x}	SE	Ψ	γ	ε	p	
Elevation	1.29	0.02							_	_	+		
Slope	4.94	0.19							_	_	+		
Terrain Ruggedness	0.23	0.34							_	_		_	
Forest	0.25	0.01							+	+	_	-/+	
Low-use 2wd roads	0.38	0.01							-/+	-/+	-/+	+	
Low-use 4wd roads	0.14	0.01							-/+	-/+	-/+	+	
Bull elk harvest			0.04	0.003	0.03	0.001	0.03	0.001	+	+	_		
Buck deer harvest			0.17	0.003	0.16	0.003	0.15	0.003	+	+	-		
Hunter effort elk			2.38	0.12	2.55	0.13	2.42	0.12			+		
Hunter effort deer			2.91	0.11	3.12	0.12	3.01	0.11			+		
Cattle			5.94	0.11	6.48	0.12	6.50	0.12	_	_	+		

Sheep	0.77	0.04	0.80	0.04	0.75	0.04	_	_	+
$\overline{\chi}_{wolf}$	1.05	0.06	1.72	0.09	1.89	0.14	-	+	_

^a Elevation = km; slope = degrees; forest = % forest cover in a 600km^2 patch; low-use 2wd roads and 4wd roads = km of low-use 2-wheel drive or 4-wheel drive roads per km²; bull elk harvest and buck deer harvest = bull elk or buck deer harvest per km²; hunter effort elk and hunter effort deer = hunter days for elk or deer per km²; cattle and sheep = cattle or sheep per km²; \overline{x}_{wolf} = mean number of wolves seen by hunters in a patch.

^b In some cases, we hypothesized that a particular covariate may be positively or negatively associated with occupancy, local colonization, local extinction, or detection. See Appendix C for expanded description of biological hypotheses.

Table 2. Example of raw hunter survey data sorted by 600km² grid cell for 2008 (black text). This table (A) shows hunter survey data for grid cells 159-161. Each row represents an individual hunter observation. In this example, at least 3 observers need to see wolves in a given week to get a "1". After building the encounter histories (blue text) from the raw hunter survey data (black text), the spreadsheet was collapsed so each grid cell has 1 row containing the encounter histories(B) and each grid cell had 1 row containing associated data (C). Data in (B) and (C) were input into Program PRESENCE.

1	١
	٦.

cell descriptionwolves 1 2 3 4 5seenBLUE Nov 3				Encounter History -2008				Wolves seen				
Seen Seen	Grid	Site	Date	#	Wk	Wk	Wk	Wk	Wk	\bar{x}	SD	Max
BLUE	cell	description		wolves	1	2	3	4	5			
159 CREEK 17												
2 Mi S of				3								
159 Bull Lake Nov21	159		17		0	0	0	0	0	3.71	1.80	7
Cabinet				7								
159 basin	159		Nov21	_								
pilgram 2				3								
159	159		Nov2	_								
berryymoun				2								
159 tain Nov14 159 Bull River Oct28 5 South Fork 4 of Bull 159 River Oct26 160 Camp Creek Nov17 6 0 0 0 0 0 3.40 1.94 6 160 bull lake Nov3 2 1 mile of 5 160 bull lake Nov11 ross creek 2 near 160 kootenai Oct29 spruce lake 2 160 drainage Oct28 161 goat mnt Nov18 9 0 0 1 0 0 3.60 3.13 10 N Fork of 2 161 Ruby Creek Nov25 Preacher 2 Mtn 161 Drainage Nov6 near yack 2	159		Nov9	2								
159 Bull River Oct28 5 South Fork 4 of Bull 159 River Oct26 160 Camp Creek Nov17 6 0 0 0 0 0 3.40 1.94 6 160 bull lake Nov3 2	1.50		NT 14	2								
South Fork of Bull 159 River Oct26 160 Camp Creek Nov17 6 0 0 0 0 0 3.40 1.94 6 160 bull lake Nov3 2 1 mile of 5 160 bull lake Nov11 ross creek 2 near 160 kootenai Oct29 spruce lake 2 160 drainage Oct28 161 goat mnt Nov18 9 0 0 1 0 0 3.60 3.13 16 N Fork of 2 161 Ruby Creek Nov25 Preacher 2 Mtn Mtn 161 Drainage Nov6 near yack 2 Nov6 Nov6				_								
of Bull 159 River Oct26 160 Camp Creek Nov17 6 0 0 0 0 0 3.40 1.94 6 160 bull lake Nov3 2 1 mile of 5 160 bull lake Nov11 ross creek 2 near 160 kootenai Oct29 spruce lake 2 161 goat mnt Nov18 9 0 0 1 0 0 3.60 3.13 10 N Fork of 2 161 Ruby Creek Nov25 Preacher 2 Mtn 161 Drainage Nov6 near yack 2	159		Oct28									
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1 mile of 5 bull lake Nov11 ross creek 2 near 160 kootenai Oct29 spruce lake 2 160 drainage Oct28 161 goat mnt Nov18 9 0 0 1 0 0 3.60 3.13 10 N Fork of 2 Ruby Creek Nov25 Preacher 2 Mtn 161 Drainage Nov6 near yack 2		-			0	0	0	0	0	3.40	1.94	6
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near 160 kootenai Oct29 spruce lake 2 160 drainage Oct28 161 goat mnt Nov18 9 0 0 1 0 0 3.60 3.13 10 N Fork of 2 161 Ruby Creek Nov25 Preacher 2 Mtn 161 Drainage Nov6 near yack 2	160		NovII	2								
160 kootenai Oct29 spruce lake 2 160 drainage Oct28 161 goat mnt Nov18 9 0 0 1 0 0 3.60 3.13 10 N Fork of 2 161 Ruby Creek Nov25 Preacher 2 Mtn Nov6 near yack 2				2								
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161 goat mnt Nov18 9 0 0 1 0 0 3.60 3.13 10 N Fork of 2 161 Ruby Creek Nov25 Preacher 2 Mtn 161 Drainage Nov6 near yack 2	160	•	0~420	2								
N Fork of 2 Ruby Creek Nov25 Preacher 2 Mtn 161 Drainage Nov6 near yack 2		_		0	0	0	1	0	0	2.60	2.12	10
161 Ruby Creek Nov25 Preacher 2 Mtn 161 Drainage Nov6 near yack 2	161	_	Nov18		Ü	U	1	U	U	3.60	3.13	10
Preacher 2 Mtn 161 Drainage Nov6 near yack 2	1.61		NI25	2								
Mtn 161 Drainage Nov6 near yack 2	101	•	NOV25	2								
161 Drainage Nov6 near yack 2				2								
near yack 2	161		Nov.6									
· · · · · · · · · · · · · · · · · · ·	101	•	TAOAO	2								
1011 IIIIIII 11110 III INDV4	161	•	Nov4	<i>L</i>								
				2								
161 pine creek Nov4 2	101	pine creek	11014	<i>L</i>								

	S. of Falls		2	
	Creek right			
	below			
161	Grand Bar	Nov9		
	preacher		2	
161	mountain	Nov10		
	north fork		10	
	of brien			
161	creek	Nov10		
	calahan		3	
161	creek	Oct26		
		Oct26	2	
	on yack	7		
161	mountain			

B. Final encounter history database.

Grid					
Cell	wk1	wk2	wk3	wk4	wk5
159	0	0	0	0	0
160	0	0	0	0	0
161	0	0	1	0	0

C. Final datafile for grid cell specific information about numbers of wolves observed (entered as covariate in PRESENCE).

Grid			
Cell	mean	SD	max
159	3.43	1.81	7
160	4.00	1.87	6
161	3.40	2.46	10

Table 3. Top models from a multi-year occupancy analysis for gray wolf packs in Montana, 2007-2009. We considered models within 4 Δ AIC to be competitive; $\log(l)$ = maximized log-likelihood, K = number of estimable parameters, Δ AIC = differences in AIC, and ω_i = Akaike weights

Model ^a	Log(l)	K	ΔΑΙС	ω_i
ψ (forest + elevation+ low-use 2wd roads) γ (forest + bull elk harvest + \bar{x}_{wolf}) ε (\bar{x}_{wolf})	3125.40	17	0.00	0.54
p(hunter effort elk + forest + week)				
ψ (forest + elevation + low-use 2wd roads) γ (forest + bull elk harvest + \bar{x}_{wolf}) ε (\bar{x}_{wolf} +	3125.70	18	0.30	0.46
forest) <i>p</i> (hunter effort elk + forest + week)				

^a forest = % forest cover in a 600km^2 patch; elevation = km; low-use 2wd roads = km of low-use 2-wheel drive roads per km²; bull elk harvest = bull elk harvest per km²; hunter effort elk = hunter days for elk per km²; \bar{x}_{wolf} = mean number of wolves seen by hunters in a patch.

Table 4. Parameter estimates from the top model for a multi-year occupancy analysis for gray wolf packs in Montana, 2007-2009.

Parameter	Variable ^a	β	SE	Effect Size (β/SE)
Ψ	Intercept	-8.56	1.20	
	Forest	4.36	0.7	6.26
	Elevation	1.82	0.43	4.28
	Low-use 2WD roads	5.62	1.11	5.05
γ	Intercept	-4.60	0.44	
	Forest	3.08	0.54	5.73
	Bull elk harvest	14.26	3.00	4.76
	\overline{X}_{wolf}	0.58	0.13	4.63
ε	Intercept	2.09	1.00	
	$\overline{\mathcal{X}}_{wolf}$	-1.92	0.53	-3.61
p	Intercept	-2.55	0.23	
	Hunter effort elk	0.18	0.02	8.39
	Forest	1.55	0.24	6.54
	Week 1 ^b	0.39	0.15	2.60
	Week 2	0.03	0.15	0.20
	Week 3	0.79	0.15	5.27
	Week 4	-0.14	0.15	0.93

^a Forest = % forest cover in a 600km^2 patch; elevation = km; low-use 2wd roads = km of low-use 2-wheel drive roads per km²; bull elk harvest = bull elk harvest per km²; \overline{x}_{wolf} = mean

number of wolves seen by hunters in a 600km^2 patch; hunter effort elk = hunter days for elk per km².

^bWeek 5 was the reference category.

Table 5. Regression model output for predicting mean number of wolves observed for individual grid cells in a patch occupancy model framework. The regression equation used was as follows: Mean # wolves seen(for individual grid cell) = β (intercept) + β (forest) + β (elevation) + β (lowuse 2WD roads) + β (year) + β (bull elk harvest) + β (depredation removals). (R² = 0.271, F = 127.60, df= 6, p <0.0005).

Parameter ^a	β	SE	t	P	Lower	Upper
					95%	95%
Intercept	-1.50	0.23	-6.60	0.00	-1.94	-1.05
Forest	2.58	0.22	11.66	0.00	2.14	3.01
Elevation	0.68	0.15	4.42	0.00	0.38	0.97
Bull elk harvest	12.57	1.70	7.39	0.00	9.23	15.90
Low-use 2WD roads	0.62	0.24	2.61	0.01	0.16	1.09
Depredation removals	0.08	0.09	0.93	0.35	-0.09	0.25
Year	0.45	0.06	7.49	0.00	0.33	0.57

^a Forest = % forest cover in a 600km² patch; elevation = km; low-use 2wd roads = km of low-use 2-wheel drive roads per km²; bull elk harvest = bull elk harvest per km²; depredation removals = # wolves removed per km² calculated for individual counties in Montana.

Figure 1. Map of Montana showing 600 km² grid cells used to estimate patch occupancy probabilities for gray wolves. Bold lines indicate Montana Fish, Wildlife, and Parks wolf management units (WMUs). Grid cells are represented by grey lines. Each 600 km² grid cell is equivalent to the average territory size of a wolf pack in Montana.

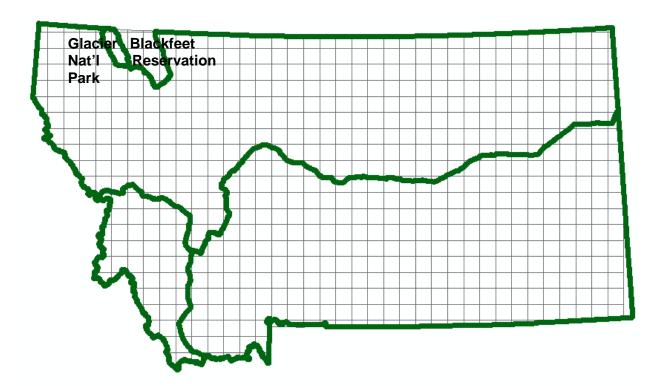


Figure 2. Patch occupancy model estimates, using hunter surveys as the sampling method, of the number of wolf packs in Montana in 2007, 2008, and 2009. Hunter survey data were divided into 4 detection criteria where a patch was only classified as occupied if ≥ 2 wolves (w) were detected by $\geq 1, \geq 2, \geq 3$, or ≥ 4 hunters (h) in a one-week sampling period. Occupancy estimates were compared to Montana Fish, Wildlife and Parks minimum known number of wolf packs in the state (N_{min}). Minimums were based on aerial surveys of radio collared wolf packs, howl, track, and scat surveys, and field verifications of public reports.

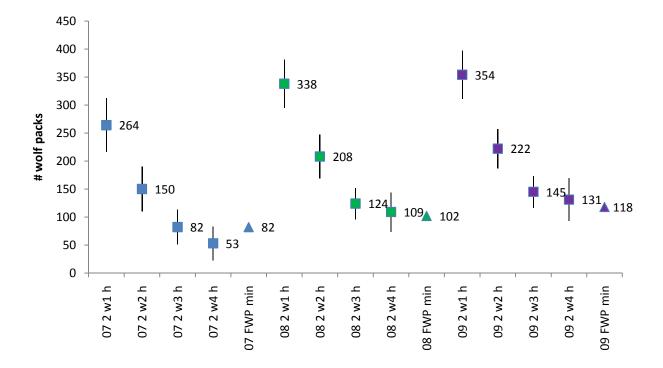


Figure 3. Patch occupancy model estimates, using hunter surveys as the sampling method, of the number of wolves in Montana in 2007, 2008, and 2009. Hunter survey data were divided into 2 detection criteria where a patch was only classified as occupied if ≥ 2 wolves (w) were detected by ≥ 2 or ≥ 3 hunters (h) in a one-week sampling period. Occupancy estimates were compared to Montana Fish, Wildlife and Parks minimum known number of wolves in the state. Minimums were based on aerial surveys of radio collared wolf packs, howl, track, and scat surveys, and field verifications of public reports.

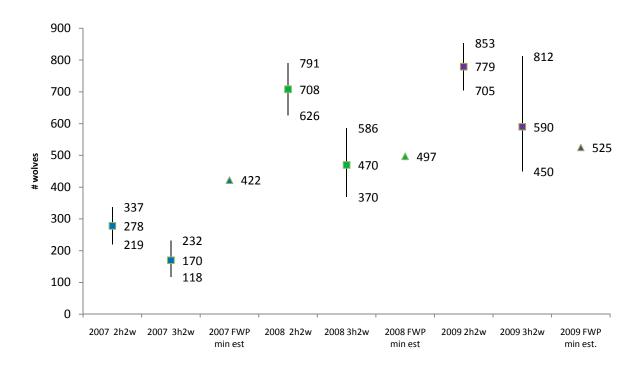
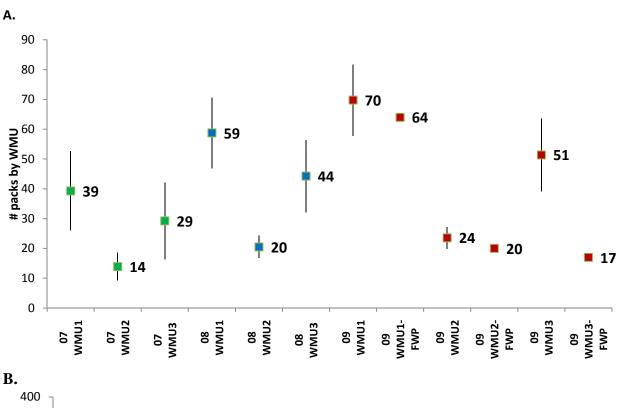


Figure 4. Patch occupancy model estimates, using hunter surveys as the sampling method, of numbers of wolf packs (A) and total numbers of wolves (B) by wolf management district (WMU), 2007-2009, Montana. Montana Fish, Wildlife, and Parks minimum estimates are provided for 2009, but were not available for 2007-2008.



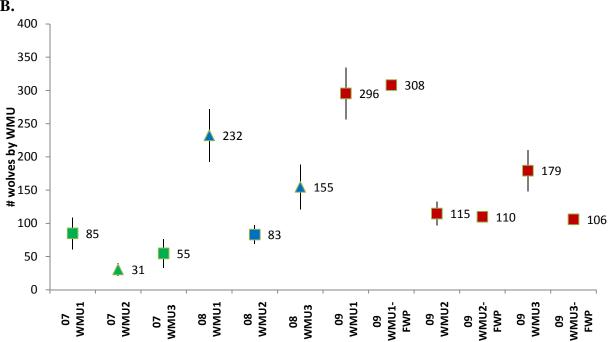
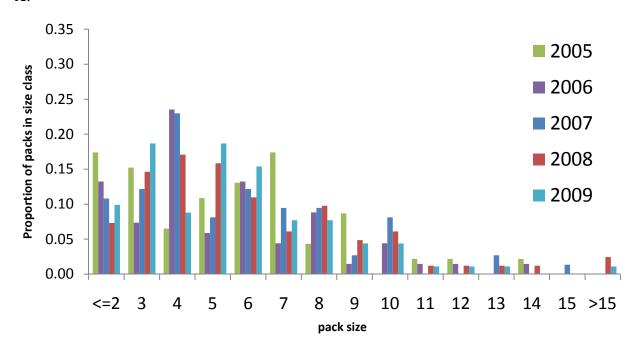


Figure 5. Distribution of gray wolf pack sizes in Montana for (A) known wolf packs statewide, 2005-2009 and (B) hunter observations in 600 km² grid cells, 2007-2009. **A**.



B.

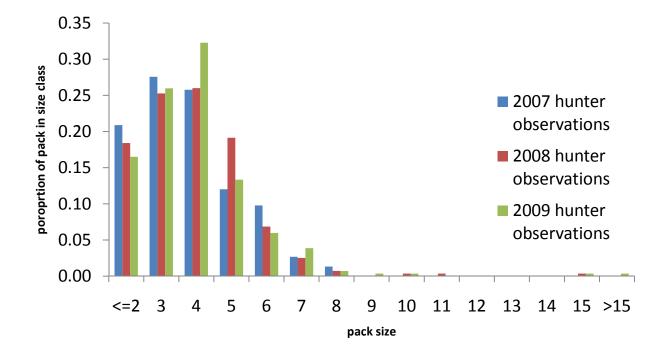
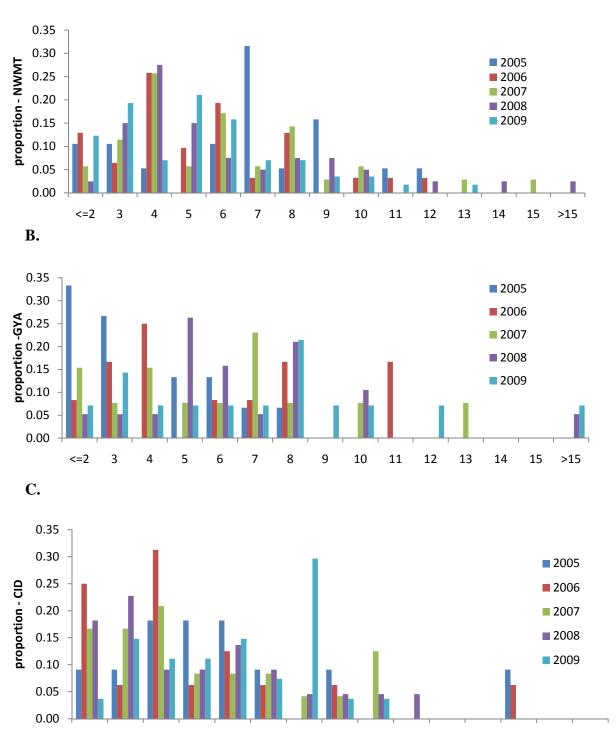


Figure 6. Distribution of known wolf pack sizes by federal gray wolf recovery areas in Montana: (A) Northwest Montana Recovery Area (NWMT), (B) Greater Yellowstone Recovery Area (GYA), and (C) Central Idaho Recovery Area (CID), 2005-2009.

A.



<=2

>15

Figure 7. Number of breeding pairs of gray wolves in Montana based on estimates of # packs derived from patch occupancy models and pack size distributions from known wolf packs in the state. For each pack of a given size, probability of containing a breeding pair was derived using methods described by Mitchell et al. (2008).

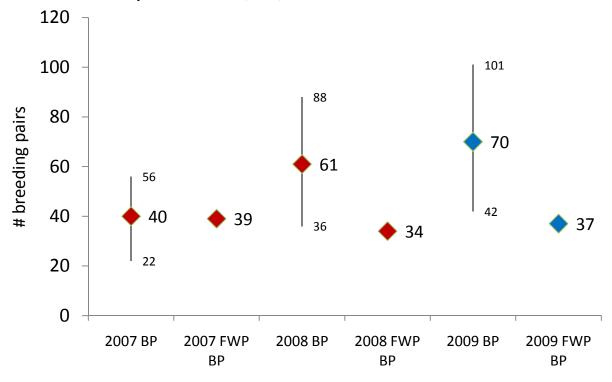
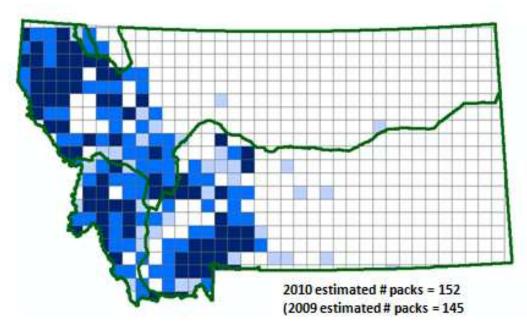
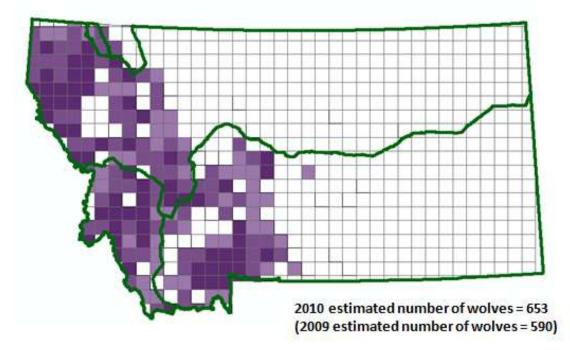


Figure 8. Projected estimates for number of wolf packs (A) and total number of wolves (B) in Montana for 2010. Occupancy values were estimated using the top model for 2007-2009 and mean wolf values were estimated using a linear regression model.

A.



B.



Appendix A. R-code for calculating confidence intervals for numbers of wolf packs and numbers of wolves.

****************************** FILE FOR IMPORTING DATA TO RUN MODELS- save encounter histories and covariates as .csv files. This code imports the data needed to run bootstraps for estimates of packs and estimates of total numbers of wolves (requires importing data on mean wolves, SD (mean wolves). August, 2010 # Data import script for Betsy's wolf data # Read in the .csv files for detection histories, site covariates, and # observation covariates. Create an unmarkedMultFrame. And at the end, # import mean wolves and SDs. # Read the .csv files. Note that the .csv filenames have an underscore # in them, but R objects do not. Note that we consider "-" (dashes) in the # .csv files to be missing values (NAs). UMARKED doesn't seem to deat with # missing values though. # Input files should all be in same order (by gridcell). wolf.histories <- read.csv("wolfdata_histories.csv", header=T, na.strings="-") wolf.sitecovs <- read.csv("wolfdata_static_sitecovs.csv", header=T,</pre> na.strings="-") #wolf.year.sitecovs <- read.csv("wolfdata_year_sitecovs.csv", header=T,</pre> na.strings="-") wolf.obscovs <- read.csv("wolfdata_obscovs.csv", header=T, na.strings="-")</pre> # top model structure - multiyear - 30sep2010: psi(forest +2wdr+ elev)gamma(meanwolf+forest+bull) #eps(meanwolf) p(elkeffort+forest+week) # Some information about the imported data: numyears <- 3 # ******** Number of years in dataset numsitecovs <- 3 # ********* Number of static site covariates, forest, roads, elevation numyrcovs <- 3 # ********* Number of year-varying site covariates numobscovs <- 4 # ********* Number of observation covariates, # Note: you only need to import the covariates present in the top model. # May need to change names of columns in sections below. # ******* End of user input ********************************* # Take a peek to make sure all imported OK. head(wolf.histories) head(wolf.sitecovs) head(wolf.year.sitecovs) head(wolf.obscovs) # Look again. See if the names are what we want. Make each imported # data object into the class needed by unmarkedMultFrame (matrix or data frame).

wolf.histories <- as.matrix(wolf.histories)
wolf.sitecovs <- as.data.frame(wolf.sitecovs)</pre>

```
wolf.obscovs <- as.data.frame(wolf.obscovs)</pre>
wolf.year.sitecovs <- as.data.frame(wolf.year.sitecovs)</pre>
head(wolf.histories)
head(wolf.sitecovs)
head(wolf.obscovs)
# Format observation covariates for the unmarkedMultFrame
tmpobs <- as.matrix(wolf.obscovs)</pre>
wolf.obscovs.formatted <- NULL
wolf.week <- NULL
wolf.mean <- NULL</pre>
wolf.elkeff <- NULL
wolf.bull <- NULL
numsites <- length(wolf.histories[ ,1])</pre>
for (i in 1:numsites){
wolf.week <- append(wolf.week, tmpobs[i,2:16])</pre>
wolf.mean <- append(wolf.mean, tmpobs[i,17:31])</pre>
wolf.elkeff <- append(wolf.elkeff, tmpobs[i,32:46])</pre>
wolf.bull <- append(wolf.bull, tmpobs[i,47:61])</pre>
wolf.obscovs.formatted <- cbind(wolf.week, wolf.mean, wolf.elkeff, wolf.bull)</pre>
dimnames(wolf.obscovs.formatted) <- list(NULL, c("week", "mean", "elkeff",</pre>
"bull"))
wolf.obscovs.formatted <- as.data.frame(wolf.obscovs.formatted)</pre>
head(wolf.obscovs.formatted)
# Format yearly site covariates:
# Format site covariates into yearlySiteCovs for unmarkedMultFrame.
vec <- NULL
mat3 <- NULL
tmpyrscovs <- as.matrix(wolf.year.sitecovs[ ,-1])</pre>
numsites <- length(wolf.histories[ ,1])</pre>
for (n in 1:numsites) {
      mat <- NULL
      for(cv in 1:numyrcovs){
      ifelse(cv==1, indbegin <- 1, indbegin <- indbegin+numyears)</pre>
      indend <- indbegin+(numyears-1)</pre>
      vec <- tmpyrscovs[n,indbegin:indend]</pre>
      mat <- cbind(mat, vec)</pre>
mat3 <- rbind(mat3, mat)</pre>
dimnames(mat3) <- list(NULL, c("bull", "elk", "mean"))</pre>
wolf.yr.sitecovs <- as.data.frame(mat3)</pre>
head(wolf.yr.sitecovs)
# Assemble the unmarked data frames
# need the unmarked library
library(unmarked)
# Strip unneeded gridcell ID column from detection histories and site
covariates.
wolf.histories <- wolf.histories[ ,-1]</pre>
wolf.sitecovs <- wolf.sitecovs[ ,-1]</pre>
# The all years data frame, this is an unmarkedMultiFrame object.
```

```
umf <- unmarkedMultFrame(wolf.histories, wolf.sitecovs,</pre>
wolf.obscovs.formatted, 3, wolf.yr.sitecovs)
# Import mean wolf values and their SDs.
wolf.means <- read.csv("wolfmeanandse.csv", header=T)</pre>
names(wolf.means) <- c("gridcell", "mean07", "sd07", "mean08", "sd08",</pre>
"mean09", "sd09")
wolf.means <- as.data.frame(wolf.means)</pre>
# Clean up.
rm(tmpobs, tmpyrscovs, i, numsitecovs, numsites, numyears,
numyrcovs, wolf.week, cv, n,
vec, mat, mat3, indbegin, indend, numobscovs)
***********************************
BOOTSTRAPPING FOR PACKS – sum of psis
**********************
# 4 October, 2010
# Script to make bootstrapped CIs for wolf pack abundance. Modified by Betsy
now that umarked can project
# correctly for colext models (yay!)
# Bootstrap CI for psis:
# 1. Resample detection histories and associated covariates
# 2. Calc psi for given model
# 3. Save in vector(matrix) and sum.
# 4. Sum, then make a matrix of the summed values from each
iteration(resample)
# 5. Extract 2.5 and 97.5 quantiles.
# To help track time needed for bootstrap.
starttime <- Sys.time()</pre>
# Need the unmarked() library.
library(unmarked)
# Number of iterations. Use 10,000 once determine that running ok.
# start with i=5 just to make sure model runs correctly.
i = 100
# Specify the detection, colonization, extinction, and occupancy portions
# of the model formula. Each component is combined in the formula statement
# to make the model formula that is passed to the colext() function below.
# Note that formula statements need to begin with a tilde (~) and should be
# enclosed in quotation marks.
# Example: detection <- as.formula("~elkeff+forest")</pre>
detection <- as.formula("~factor(week)+elkeff+forest")</pre>
occupancy <- as.formula("~forest + elev + road2wdr")</pre>
colonization <- as.formula("~forest+bull+mean")</pre>
extinction <- as.formula("~mean")</pre>
# unmarked data frame was made from a different script.
# Note that here the unmarked data frame is named "umf".
```

```
data <- umf
# Make a copy of the data frame to avoid contamination.
bdata <- data
ns <- numSites(bdata)</pre>
out.mat <- NULL
abunds <- NULL
sums <- NULL
for(i in 1:i){
      # Get a resample of length numSites(bdata) with replacement.
      # This is done in two steps using indices from the sample() function.
      ind <- sample.int(ns, ns, replace=T)</pre>
      bdata.ind <- bdata[ind, ]</pre>
      # Fit a specified model to the resampled data.
      msoccmod <- colext(occupancy, colonization, extinction, detection,
      data=bdata.ind, control=list(maxit=5000))
      # Get psi estimates for each row for each year.
      # Array indices: mod@projected[parameter(1=p,2=psi), year, site]
      projecteds <- msoccmod@projected[2,1:3, ]</pre>
      preds <- t(projecteds)</pre>
      # Get meanwolves value for each year -don't need this for pack CIs.
      #wolf.means.ind <- wolf.means[ind, ]</pre>
      #rwolves07 <- rnorm(ns, wolf.means.ind$mean07,</pre>
                                                       wolf.means.ind$sd07)
      #rwolves08 <- rnorm(ns, wolf.means.ind$mean08, wolf.means.ind$sd08)</pre>
      #rwolves09 <- rnorm(ns, wolf.means.ind$mean09, wolf.means.ind$sd09)</pre>
      #rwolves <- cbind(rwolves07, rwolves08, rwolves09)</pre>
      # Remove zeros from rwolves.
      #mwolves <- ifelse(rwolves<0, 0, rwolves)</pre>
      # Multiply meanwolves by psi.
      multed <- preds
      # Sum columns of out.mat to get abundance estimate from each resample.
      abunds <- apply(multed, 2, sum)
      # Build a matrix of summed psi*meanwolves values (rows = #iterations)
      sums <- rbind(sums, abunds)</pre>
# use quantiles to find CIs.
wolf.ci <- NULL
for (y in 1:3){
ci \leftarrow quantile(sums[,y], probs = c(0.025, 0.050, 0.075, 0.100, 0.125, 0.500,
0.0875, 0.900, 0.925, 0.950, 0.975))
wolf.ci <- rbind(wolf.ci, ci)</pre>
dimnames(wolf.ci) <- list(c("2007", "2008", "2009"), c("2.5%", "5.0%", "7.5%"
,"10%", "12.5%", "50%", "87.5%", "90%","92.5%","95.0%","97.5%"))
wolf.ci
# Record how long it takes to run bootstraps.
```

```
endtime <- Sys.time()</pre>
runtime <- endtime - starttime
runtime
# Clean up.
#rm(occupancy, colonization, extinction, detection, data, bdata, ns, out.mat,
#i, ind, bdata.ind, msoccmod, preds, abunds, starttime, endtime, runtime, ci,
#y, multed, rwolves, mwolves, sums, rwolves07, rwolves08, rwolves09,
projecteds)
***********************************
Bootstrap program for # wolves (psi*mean)
# 1 October, 2010
# Script to make bootstrapped CIs for wolf abundance. Modified by Betsy now
that umarked can project
# correctly for colext models (yay!)
# Bootstrap CI for psi*meanwolves:
# 1. Resample detection histories and associated covariates
# 2. Calc psi for given model
# 3. Multiply by associated (resampled) meanwolves drawn from a
# normal dist. of mean, sd per gridcell.
# 4. Save in vector(matrix) and sum.
# 5. Sum, then make a matrix of the summed values from each
iteration(resample)
# 5. Extract 2.5 and 97.5 quantiles.
# To help track time needed for bootstrap.
starttime <- Sys.time()</pre>
# Need the unmarked() library.
library(unmarked)
# Number of iterations.
i = 100
# Specify the detection, colonization, extinction, and occupancy portions
# of the model formula. Each component is combined in the formula statement
# to make the model formula that is passed to the colext() function below.
# Note that formula statements need to begin with a tilde (~) and should be
# enclosed in quotation marks.
# Example: detection <- as.formula("~elkeff+road2wdr")</pre>
detection <- as.formula("~factor(week)+elkeff+forest")</pre>
occupancy <- as.formula("~forest + elev + road2wdr")</pre>
colonization <- as.formula("~forest+bull+mean")</pre>
extinction <- as.formula("~mean")</pre>
# unmarked data frame was made from a different script.
# Note that here the unmarked data frame is named "umf".
data <- umf
# ***********************************
```

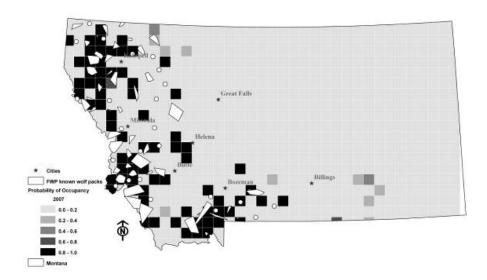
```
# Make a copy of the data frame to avoid contamination.
bdata <- data
ns <- numSites(bdata)</pre>
out.mat <- NULL
abunds <- NULL
sums <- NULL
for(i in 1:i){
             # Get a resample of length numSites(bdata) with replacement.
             # This is done in two steps using indices from the sample() function.
             ind <- sample.int(ns, ns, replace=T)</pre>
             bdata.ind <- bdata[ind, ]</pre>
             # Fit a specified model to the resampled data.
             msoccmod <- colext(occupancy, colonization, extinction, detection,
             data=bdata.ind, control=list(maxit=5000))
             # Get psi estimates for each row for each year.
             # Array indices: mod@projected[parameter(1=p,2=psi), year, site]
             projecteds <- msoccmod@projected[2,1:3, ]</pre>
             preds <- t(projecteds)</pre>
             # Get meanwolves value for each year
             wolf.means.ind <- wolf.means[ind, ]</pre>
             rwolves07 <- rnorm(ns, wolf.means.ind$mean07, wolf.means.ind$sd07)</pre>
             rwolves08 <- rnorm(ns, wolf.means.ind$mean08, wolf.means.ind$sd08)
             rwolves09 <- rnorm(ns, wolf.means.ind$mean09, wolf.means.ind$sd09)</pre>
             rwolves <- cbind(rwolves07, rwolves08, rwolves09)</pre>
             # Remove negative values from rwolves.
             mwolves <- ifelse(rwolves<0, 0, rwolves)</pre>
             # Multiply meanwolves by psi.
             multed <- preds*mwolves</pre>
             # Sum columns of out.mat to get abundance estimate from each resample.
             abunds <- apply(multed, 2, sum)</pre>
             # Build a matrix of summed psi*meanwolves values (rows = #iterations)
             sums <- rbind(sums, abunds)</pre>
}
# use quantiles to find CIs.
wolf.ci <- NULL
for (y in 1:3){
ci \leftarrow quantile(sums[ ,y], probs = c(0.025, 0.05, 0.075, 0.1, 0.125, 0.5, 0.5, 0.075, 0.1, 0.125, 0.5, 0.5, 0.075, 0.1, 0.125, 0.5, 0.5, 0.075, 0.075, 0.1, 0.125, 0.5, 0.5, 0.075, 0.075, 0.1, 0.125, 0.5, 0.075, 0.075, 0.1, 0.125, 0.5, 0.075, 0.075, 0.1, 0.125, 0.5, 0.075, 0.075, 0.1, 0.125, 0.5, 0.075, 0.075, 0.1, 0.125, 0.5, 0.075, 0.075, 0.1, 0.125, 0.5, 0.075, 0.075, 0.1, 0.125, 0.5, 0.075, 0.075, 0.1, 0.125, 0.5, 0.075, 0.075, 0.1, 0.125, 0.5, 0.075, 0.1, 0.125, 0.5, 0.075, 0.1, 0.075, 0.1, 0.125, 0.5, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.1, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.075, 0.07
0.875, 0.90, 0.925, 0.95, 0.975))
wolf.ci <- rbind(wolf.ci, ci)</pre>
dimnames(wolf.ci) <- list(c("2007", "2008", "2009"), c("2.5%", "5.0%", "7.5%"
,"10%", "12.5%", "50%", "87.5%", "90%","92.5%","95.0%","97.5%"))
wolf.ci
endtime <- Sys.time()</pre>
runtime <- endtime - starttime
runtime
# Clean up.
```

#rm(occupancy, colonization, extinction, detection, data, bdata, ns, out.mat,
#i, ind, bdata.ind, msoccmod, preds, abunds, starttime, endtime, runtime, ci,
#y, multed, rwolves, mwolves, sums, rwolves07, rwolves08, rwolves09,
projecteds)

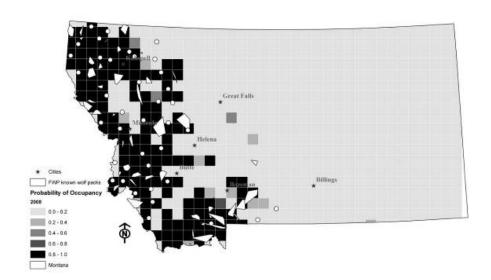
Appendix B. The probability each 600 km² patch in Montana, USA was occupied by a wolf pack (A) and the number of wolves (B) in 2007, 2008, and 2009. Occupancy probabilities were estimated using a multi-season patch occupancy model with hunter surveys as the sampling method and forest cover, low-use 2-wheel drive road density, and elevation as predictor variables. Six-hundred km² patches were used which was equal in area to mean wolf pack territory size in Montana. Montana Fish, Wildlife and Parks (MFWP) known wolf packs were based on aerial surveys of radio collared wolf packs, howl, track, and scat surveys, and field verifications of public reports.

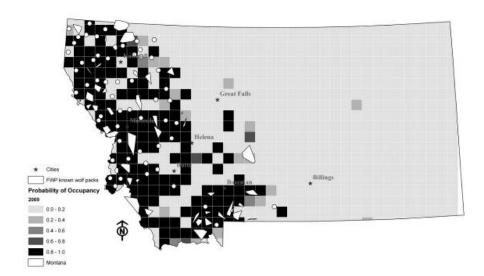
A.

2007

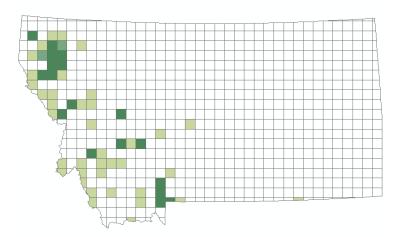


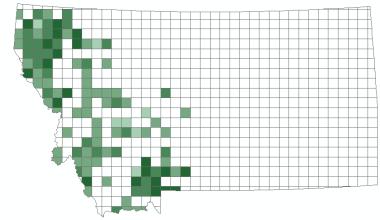
2008

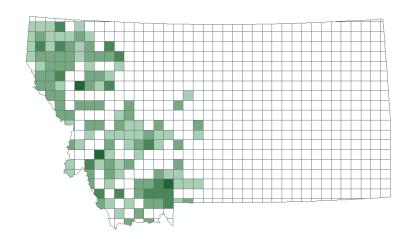




B. Shading shows cell values for (occupancy*meanwolf) ranging from 2->10. Darker colors = higher # wolves.







Appendix C. Rich, L. N. 2010. An assessment of factors influencing territory size and the use of hunter surveys for monitoring wolves in Montana. MS Thesis, University of Montana, Missoula.

(see attached)